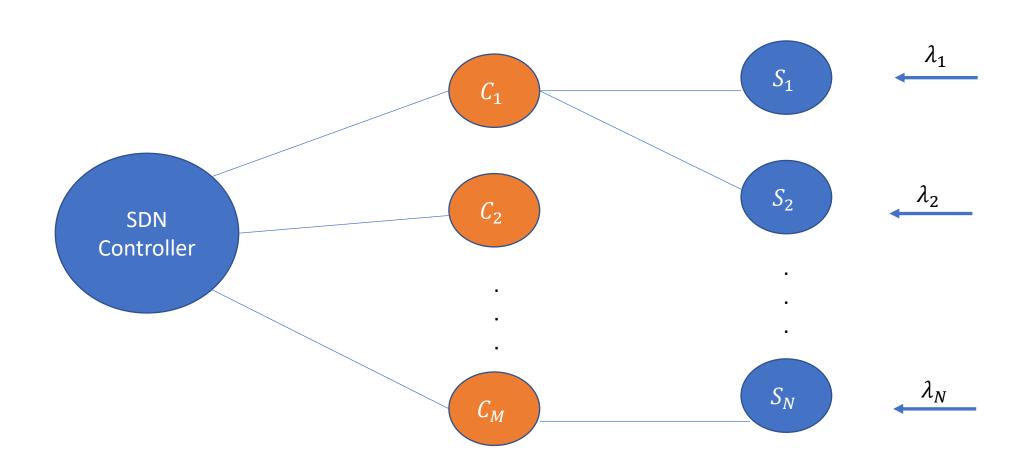
# SDN Flow Control

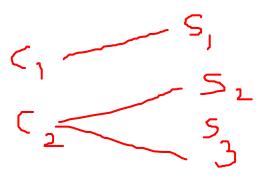


## Model and Assumptions

- Whenever there is an arrival of flow, we need to take a decision
- Flow arrives at switch i as a Poisson process with parameter  $\lambda_i$
- ullet Service time of each flow is exponentially distributed with parameter  $\mu$
- State ={Number of flows in  $C_1$ ,....., Number of flows in  $C_N$ }
- Action space for  $C_i$ ={Do nothing, Add one switch to  $C_i$ , Remove one switch from  $C_i$ }

such that all switches are accommodated in the revised allocation after the action is chosen

### Model



- Reward= r(s, a) = Some fairness metric after action a is chosen in state s
- Each switch has some limited capability to process flows. Hence, we can assume that the maximum number of flows supported by each switch is  $N_F$ .
- Transition probability
  - Example, say 2 controllers and 3 switches,  $N_F=2$
  - Under the action do nothing,  $p_{ss'}(a)=\lambda_1/(\sum_{i=1}^3\lambda_i+6\mu)$  if s=(i,j) and s'=(i+1,j)

#### Model

• Cost: c(s, a) = 0 if action is do nothing  $c(s, a) = number\ of\ switch\ exchanges\ between\ controllers\ else$ 

Objective: Maximize the discounted total reward over infinite horizon Subject to total discounted cost over infinite horizon Formulated as constrained Markov Decision Process (CMDP)

 $S_{max}$  = Constraint on average number of switch exchanges between controller

$$\max_{\pi \in U} \lim_{T \to \infty} \sum_{t=0}^{T-1} \alpha^t E_{\pi}[r(s_t, a_t)]$$

$$subject \ to \lim_{T \to \infty} \sum_{t=0}^{T-1} \alpha^t E_{\pi}[c(s_t, a_t)] \le S_{max}$$

## Q-learning

- $Q_{n+1}(s,a) = (1-a(n))Q_n(s,a) + a(n)(r(s,a) l_nc(s,a) + a(n)(r(s,a)) a(n)(s',a'))$
- $l_{n+1} = \Lambda[l_n + b(n)(S_n S_{max})]$
- Take  $a(n) = \frac{1}{n^{0.6}}$ ,  $b(n) = \frac{1}{n}$
- $\Lambda$  is a projection operator to keep the Lagrange multiplier  $l_n$  between [0,L] for a large L